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Donostia

#4 Unsupervised Learning

by Saturdays.AI

Saturdays.AI
Machine Learning

Schedule

State of the course

Session 4 Review

Challenge

Notebook + resources

State of the course

#1 Cleaning & Exploratory Data Analysis ✓

#2 Supervised Learning ✓

#3 Decision Trees & Random Forest ✓

#4 Unsupervised Learning: Clustering & Dim. Red. ● Today!

#5 Time Series Analysis + Data Viz 

#6 Neural Networks, Gradient Descent 

#7 NLP 

Questions?



Unsupervised Learning

- What is Unsupervised Learning?
- Clustering
- K-means, DBSCAN, Mean Shift
- Dimensionality Reduction
- PCA, NMF, SVD

Future of ML

Unsupervised
Learning

The future of machine learning is unsupervised learning.



Supervised
learning is the
icing on the
cake

Unsupervised
learning is the
cake itself

Humans learn mostly through unsupervised learning: we absorb vast amounts of data from our surroundings without needing a label.

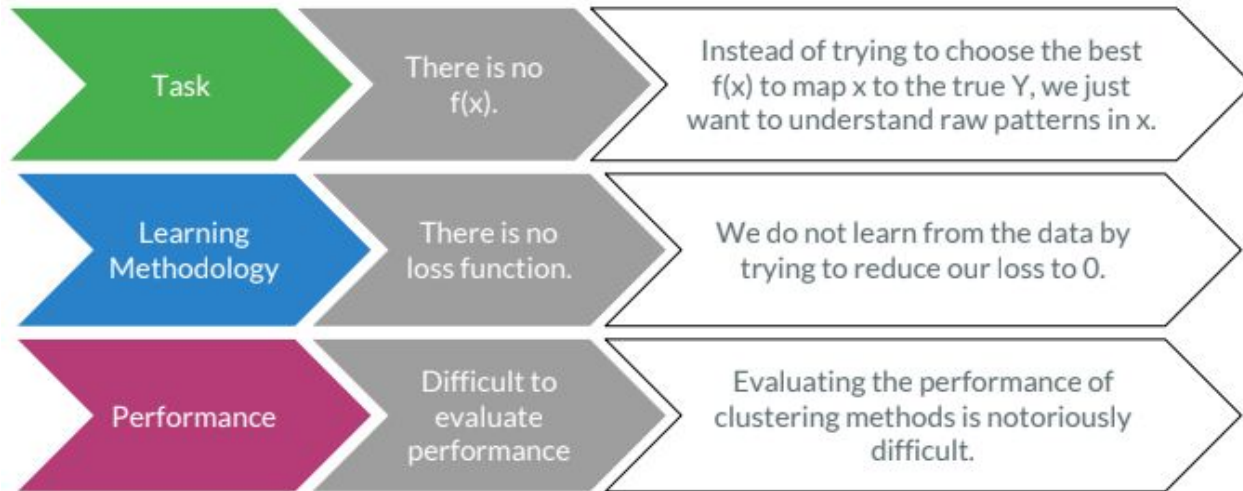
To reach true machine intelligence (i.e., a machine that thinks and learns for itself), ML needs to get better at **unsupervised** learning - it should learn without us having to feed it labels or explicit instructions.

We will have only scratched the surface in this class.



Different Framework

How is this model framework different than what we've already seen?



When we use Unsupervised Learning?

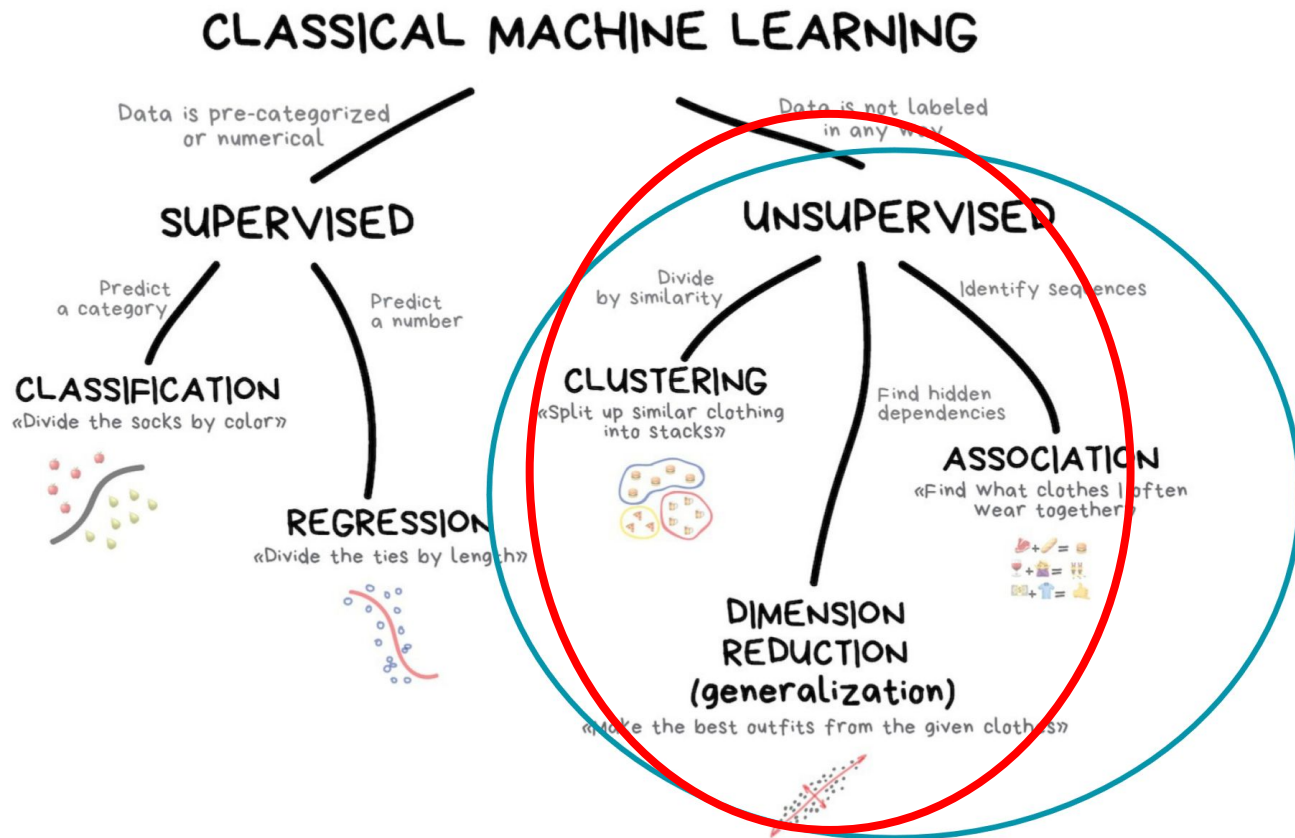
Learning
Methodology

When would I turn to
unsupervised learning?

- You have extremely high dimensional data (i.e., many features) that you want to investigate
- You have a research question but no labelled outcome feature
 - This is true for many datasets
- You want to detect any relationships or patterns in your data
 - E.g. customer behavior data
- You don't have time to dive deep into defining an outcome
 - Use unsupervised learning as first exploratory step

As the amount of data in the world grows, we will increasingly turn to unsupervised learning methods.

Where we are?



Clustering

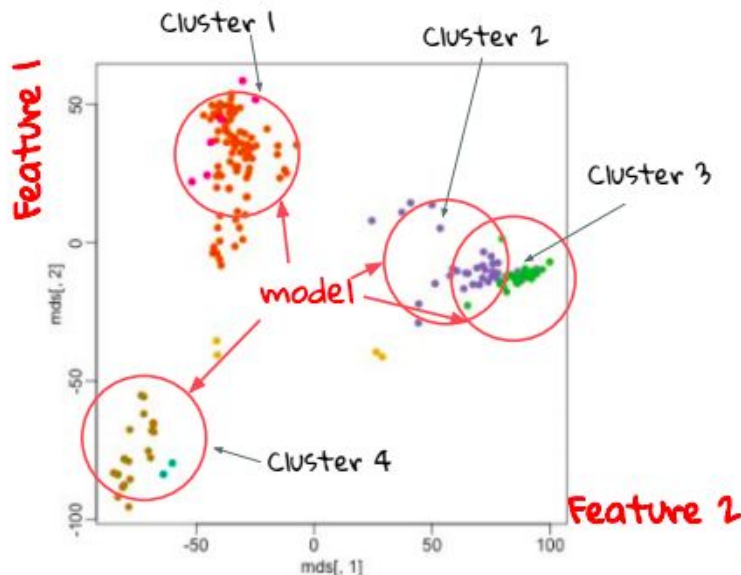
Clustering Task

Clustering is a powerful unsupervised algorithm that detects naturally occurring patterns in the data.

Clustering splits data in order to find out how observations are similar on a number of different features.

We are not predicting a true Y.

The clusters are the model.
We decide the number of clusters, represented as K.

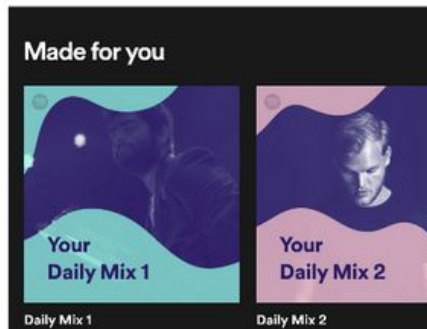


Applications of Clustering

- Customer Segmentation
- Document Clustering
- Image Segmentation
- Recommendation Engines
- and more...

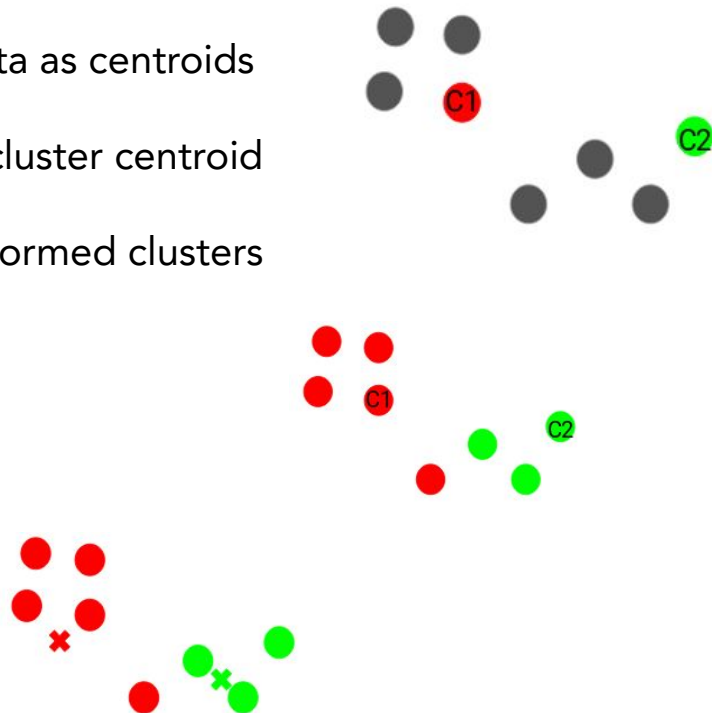


Document Clustering

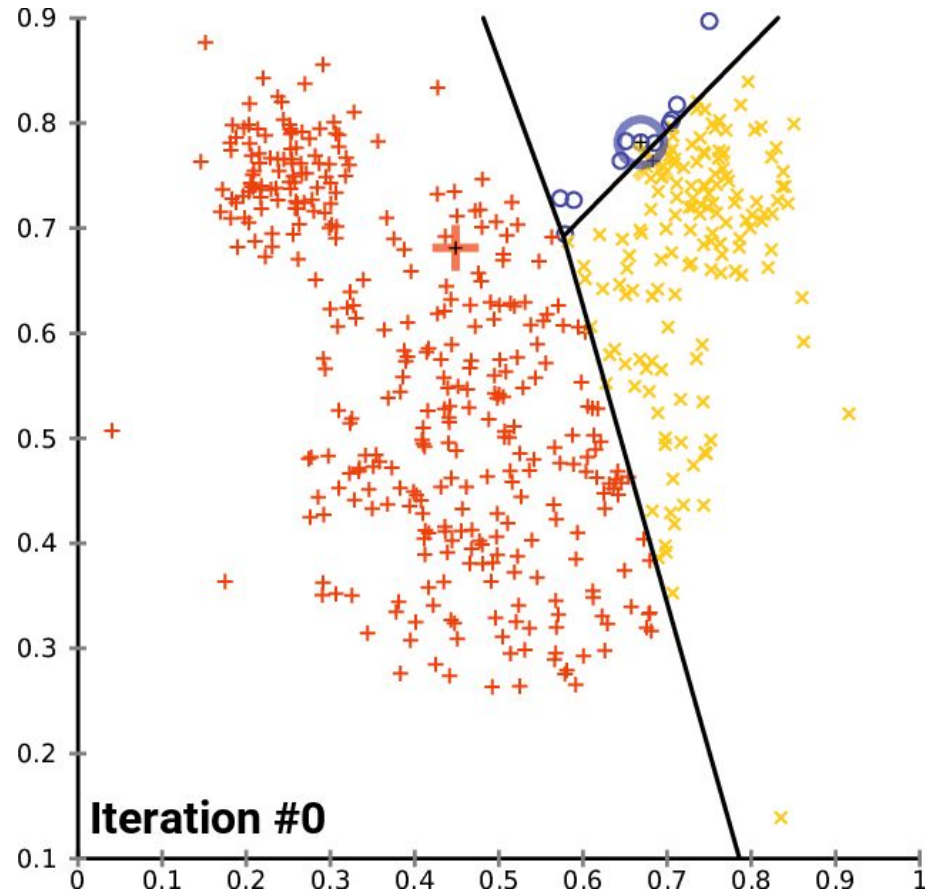


K-Means step-by-step

- Step 1: Choose the number of clusters k
- Step 2: Select k random points from the data as centroids
- Step 3: Assign all the points to the closest cluster centroid
- Step 4: Recompute the centroids of newly formed clusters
- Step 5: Repeat steps 3 and 4



K-Means step-by-step



DBSCAN

1. START arbitrary point, ϵ parameter.

Q: ¿Are there MinPts within ϵ neighborhood?

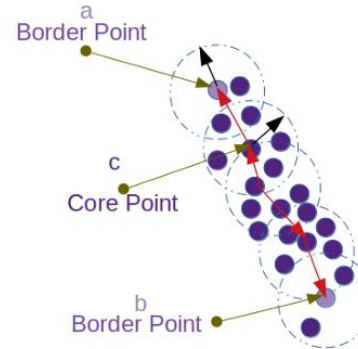
YES: cluster formation starts.

NO: the point is labeled as noise.

Concept of **density reachable** and **density connected points** are important here.

Q: ¿Is **core point**? YES: the points within the ϵ neighborhood is also part of the cluster. All the points found within ϵ neighborhood are added (with their own ϵ neighborhood, if they are also core points).

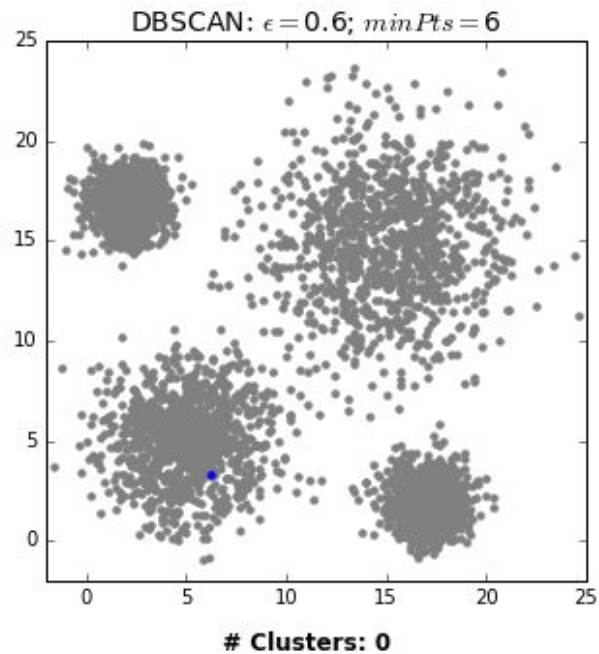
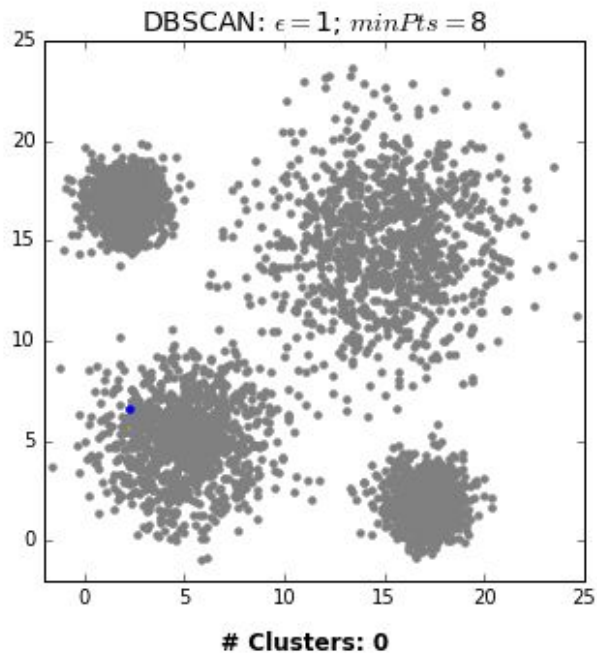
2. REPEAT. The above process continues until the density-connected cluster is completely found.
3. RESTART with a **new point** which can be a part of a new cluster or labeled as noise.



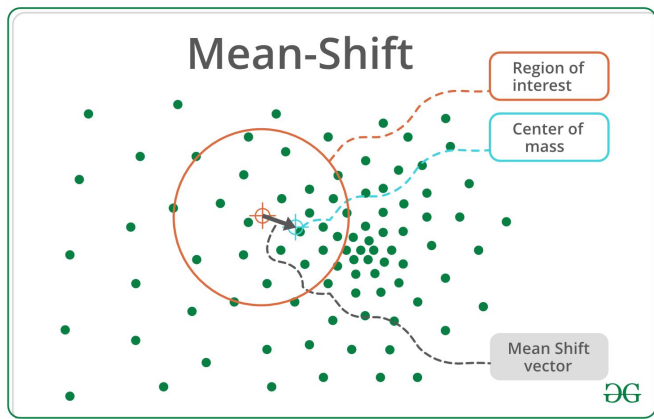
a, b are Density Reachable from a core point c.

a, b are called Density Connected points.

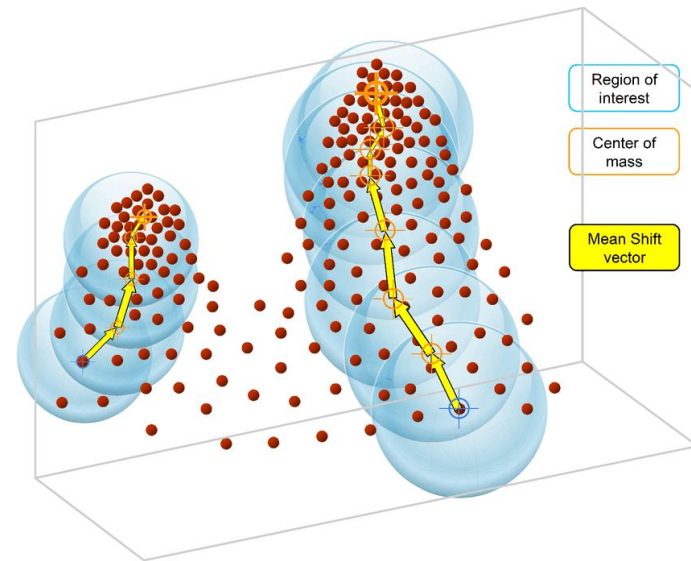
DBSCAN



Mean Shift

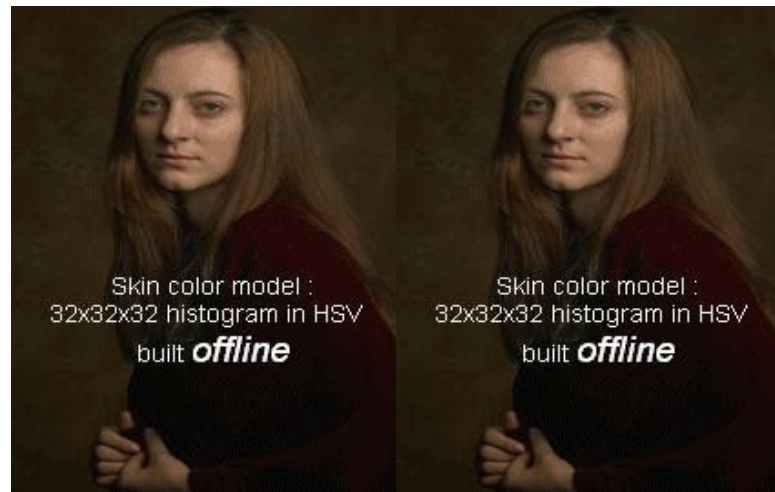
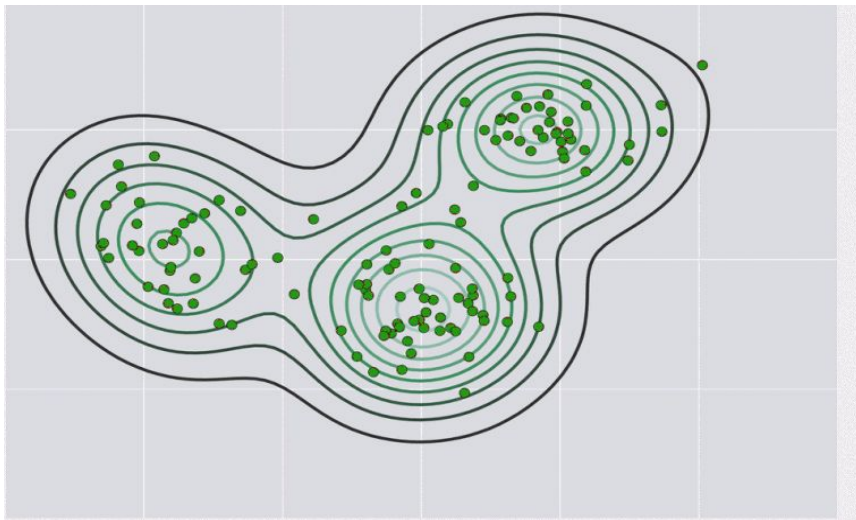


PROS: robust, data-shape agnostic
Just one (W) parameter



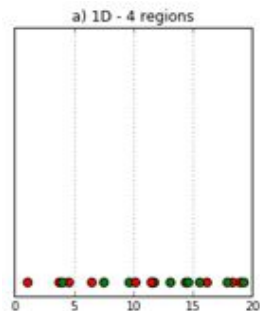
CONS: Output depends on W (not trivial)
Computationally expensive

MeanShift & example with CAM

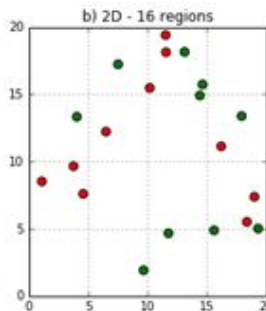


Why dimensionality reduction?

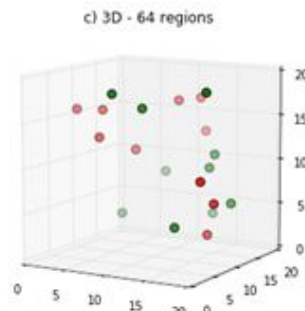
When data has a high dimension (many features), it is extremely complex to process due to inconsistencies in the features, which increase the computational time processing and requires more evolved EDA (Exploratory Data Analysis).



1D



2D



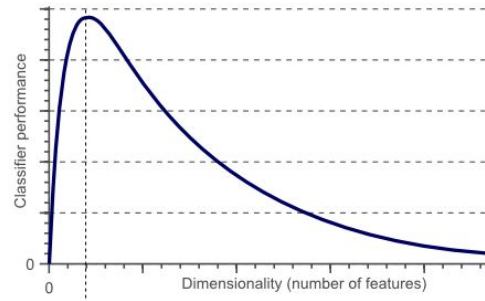
3D

???

xD

Dimensionality Reduction, Overview

- **Goal:** reduce the number of features (dimensionality) by maximizing the explained variance, to obtaining a set of principal features.
- **How does it work?:** Transforming the data in the high-dimensional space to a space in fewer dimensions.
- **Advantages:**
 - Removes inconsistencies in the features
 - Highlight relevant features, not all features are relevant to our problem
 - Avoids overfitting due to strong correlations
 - Reduces computational time and space complexity
- **Disadvantages**
 - More difficult to explain the meaning
 - We fundamentally “miss” some data



What is PCA?

Principal component analysis (PCA) is a dimensionality reduction technique that enables to identify correlations and patterns in a dataset so it can be transformed into a dataset of significant lower dimensions and keeping the most relevant information.

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)
0	5.1	3.5	1.4	0.2
1	4.9	3.0	1.4	0.2
2	4.7	3.2	1.3	0.2
3	4.6	3.1	1.5	0.2
4	5.0	3.6	1.4	0.2



	principal component 1	principal component 2
0	-2.264542	0.505704
1	-2.086426	-0.655405
2	-2.367950	-0.318477
3	-2.304197	-0.575368
4	-2.388777	0.674767

What is PCA (math definition)?

Principal component analysis (PCA) is statistical procedure that uses an **orthogonal transformation** to convert a set of observations of possibly correlated variables into a set of values of **linearly uncorrelated variables** called principal components.

PCA step by step

Standardize the data

Build the covariance matrix

Calculate the Eigenvectors and Eigenvalues

Compute Principal Components

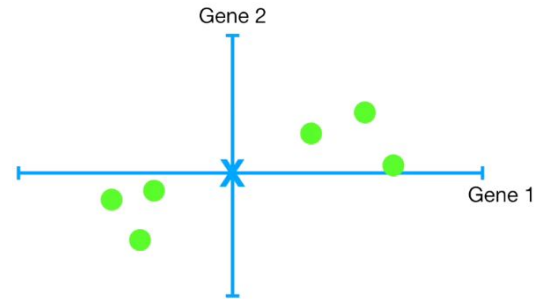
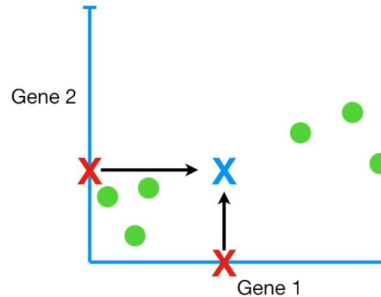
Reduce the data dimensions

	Mouse 1	Mouse 2	Mouse 3	Mouse 4	Mouse 5	Mouse 6
Gene 1	10	11	8	3	2	1
Gene 2	6	4	5	3	2.8	1

PCA step by step

Standardize the data

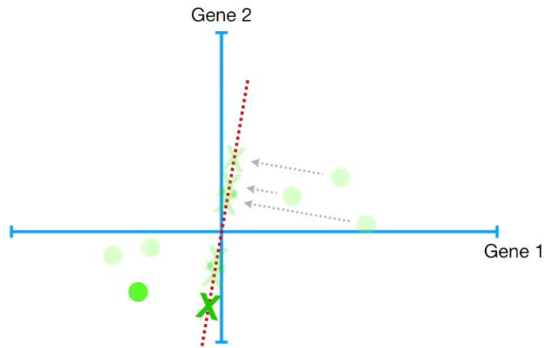
	Mouse 1	Mouse 2	Mouse 3	Mouse 4	Mouse 5	Mouse 6
Gene 1	10	11	8	3	2	1
Gene 2	6	4	5	3	2.8	1



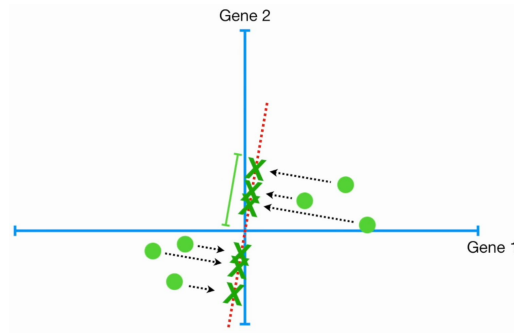
PCA step by step

Build the covariance matrix

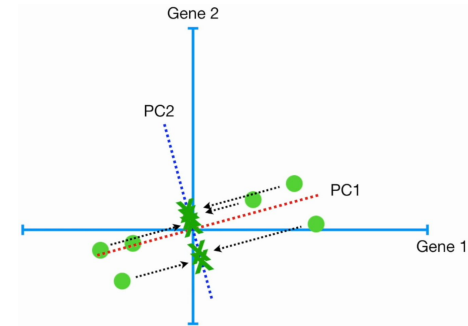
Calculate the Eigenvectors and Eigenvalues



Orthogonal transformation feature 1



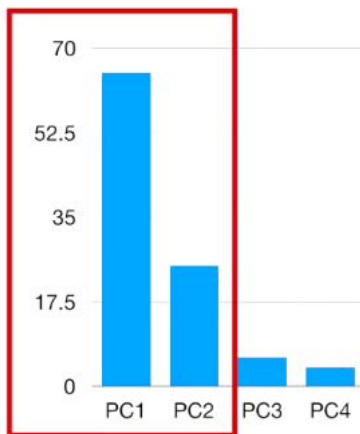
Orthogonal transformation feature 2



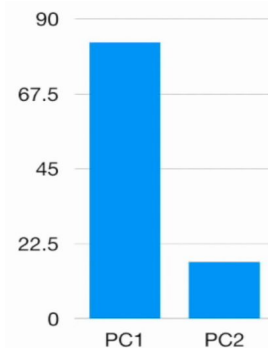
PCA step by step

Compute Principal Components Reduce the data dimensions

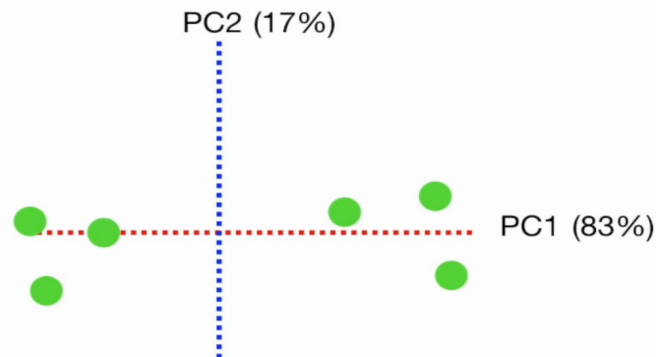
Compute Principal Components



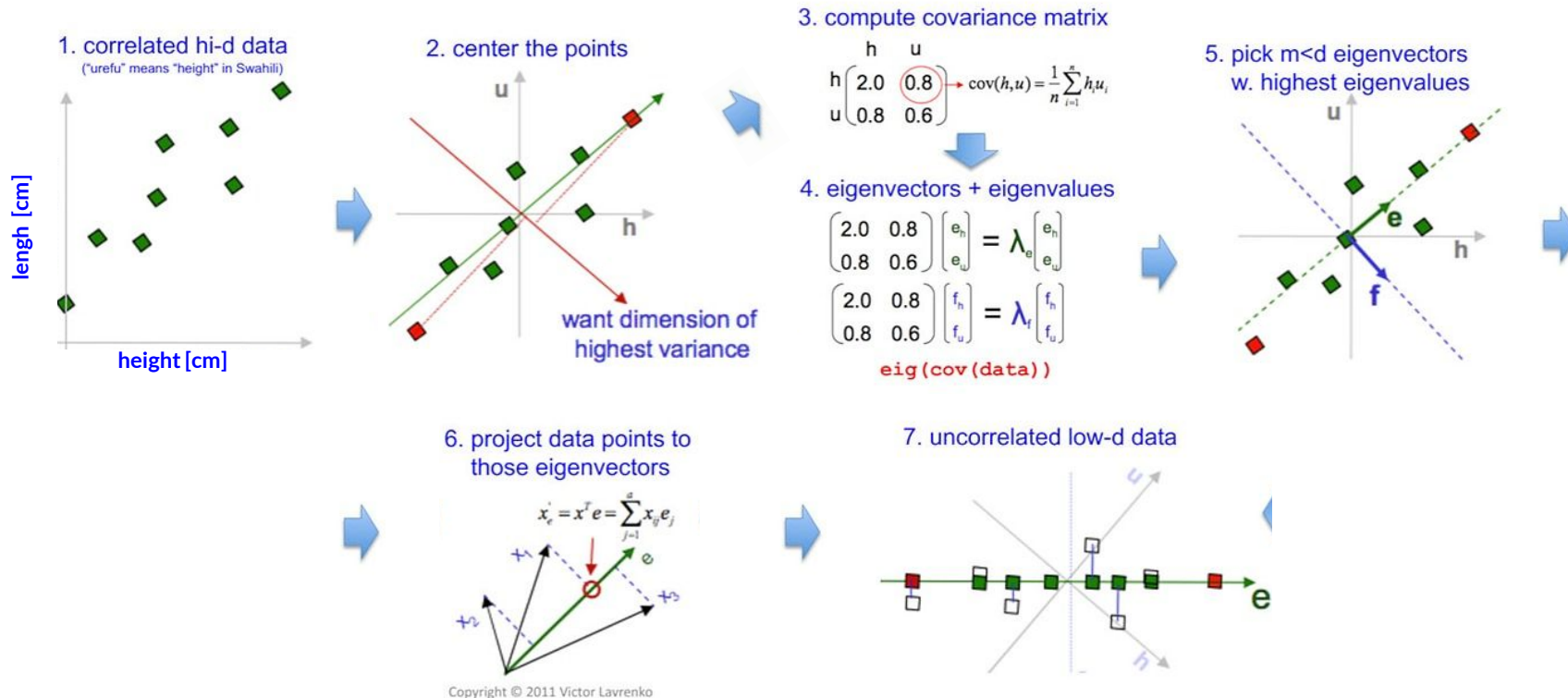
Selected PC



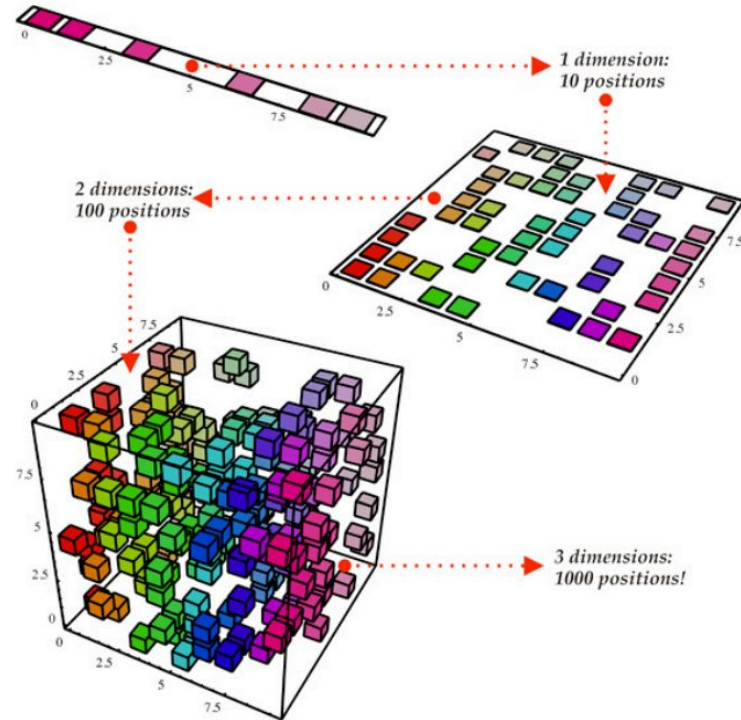
Percentages of variation (%)s



PCA summary



PCA (Intuitive way)



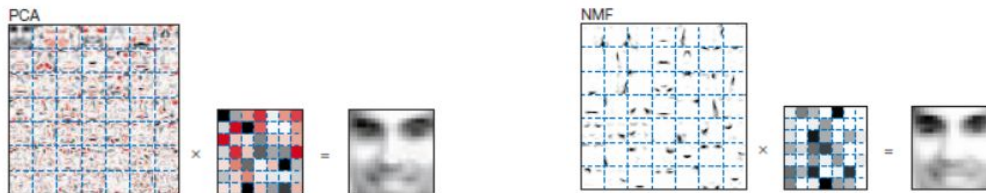
NMF (Non-Negative Matrix Factorization)

X = Datos, W = Pesos, H = Componentes

$$X = \begin{bmatrix} x_1 \\ x_2 \\ \dots \\ x_k \end{bmatrix} \quad W = \begin{bmatrix} w_1 \\ w_2 \\ \dots \\ w_k \end{bmatrix} \quad H = \begin{bmatrix} h_1 \\ h_2 \\ \dots \\ h_k \end{bmatrix} \quad \longrightarrow \quad x_i = \begin{bmatrix} w_{i1} & w_{i2} & \dots & w_{ik} \end{bmatrix} \times \begin{bmatrix} h_1 \\ h_2 \\ \dots \\ h_k \end{bmatrix} = \sum_{j=1}^k w_{ij} \times h_j$$

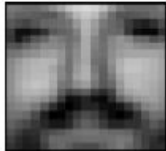
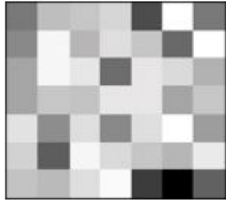


w_i : weights

components

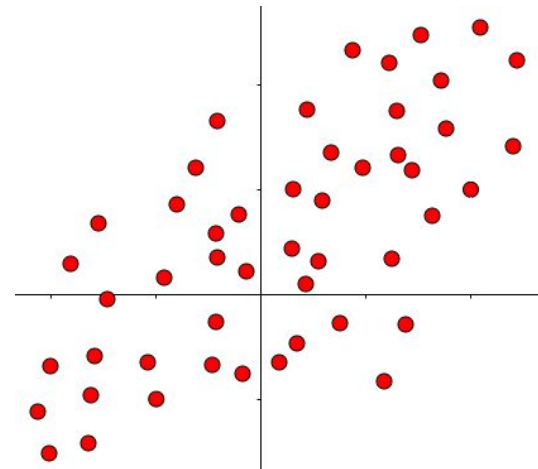
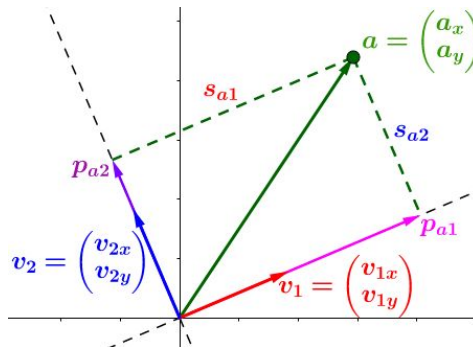
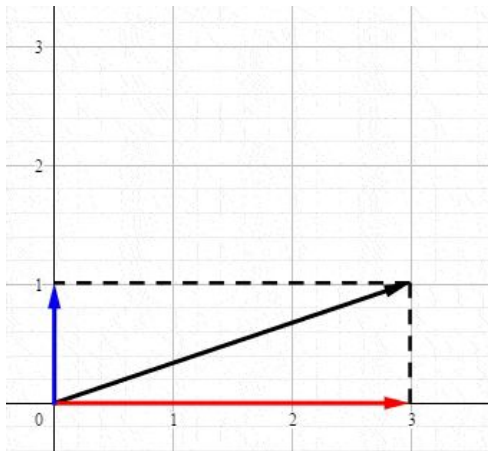


Faces (CV): Cannot be negative!

NMF (Non-Negative Matrix Factorization)

$$\underbrace{X(:, j)}_{j\text{th facial image}} \approx \sum_{k=1}^r \underbrace{W(:, k)}_{\text{facial features}} \underbrace{H(k, j)}_{\text{importance of features in } j\text{th image}} = \underbrace{WH(:, j)}_{\text{approximation of } j\text{th image}} .$$


SVD (Singular Value Decomposition)

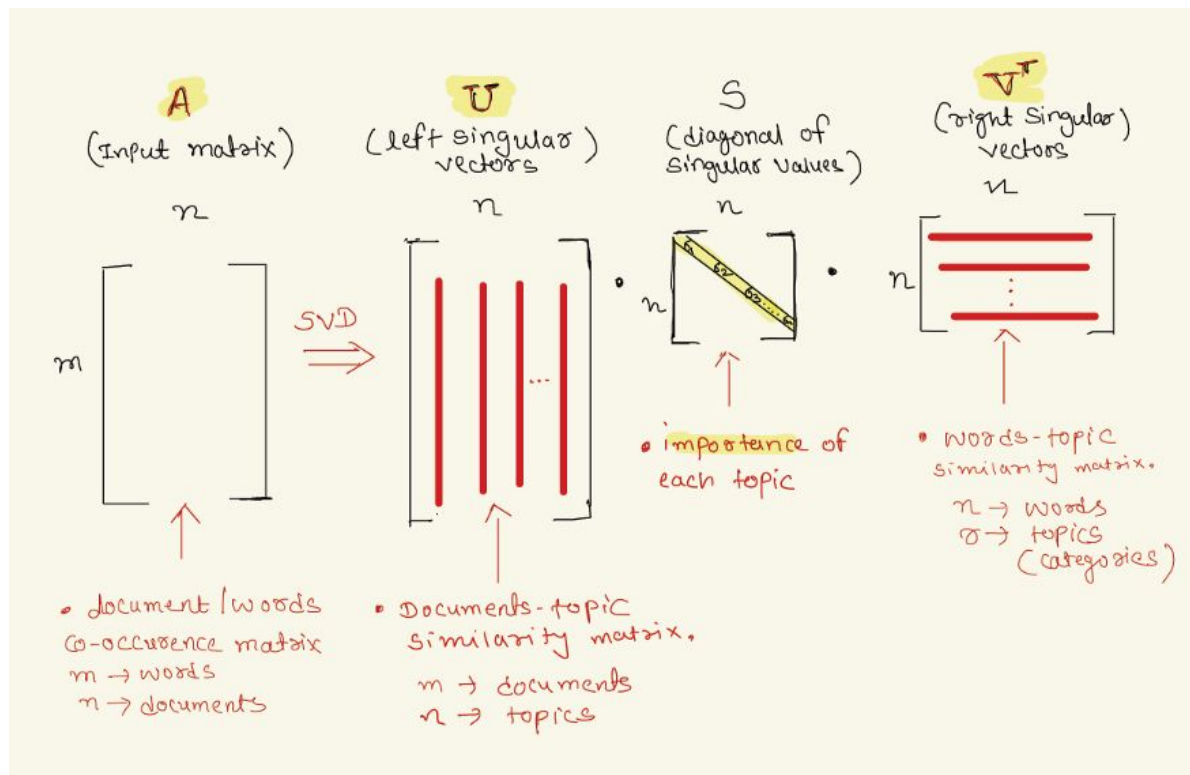


$$A \cdot V = S$$

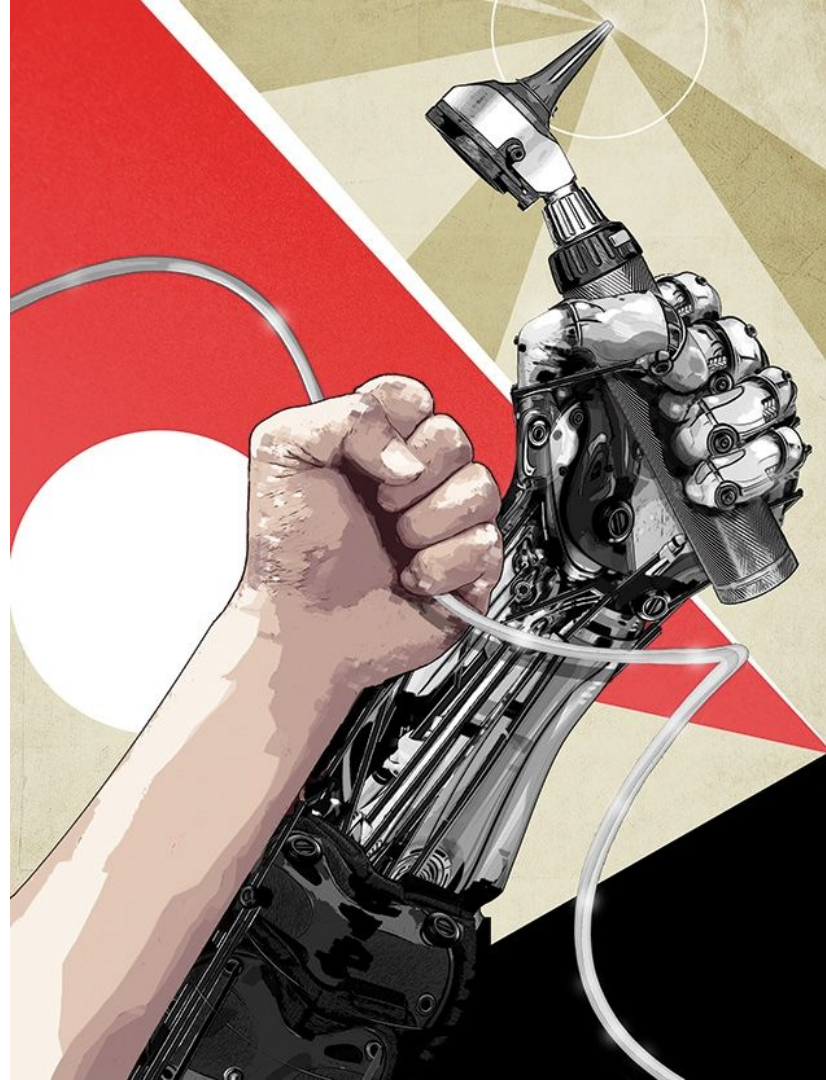
Matrix of points The dot product performs the projection Matrix of decomposition axes Matrix of the lengths of projections

$$A = S V^{-1} = S V^T$$

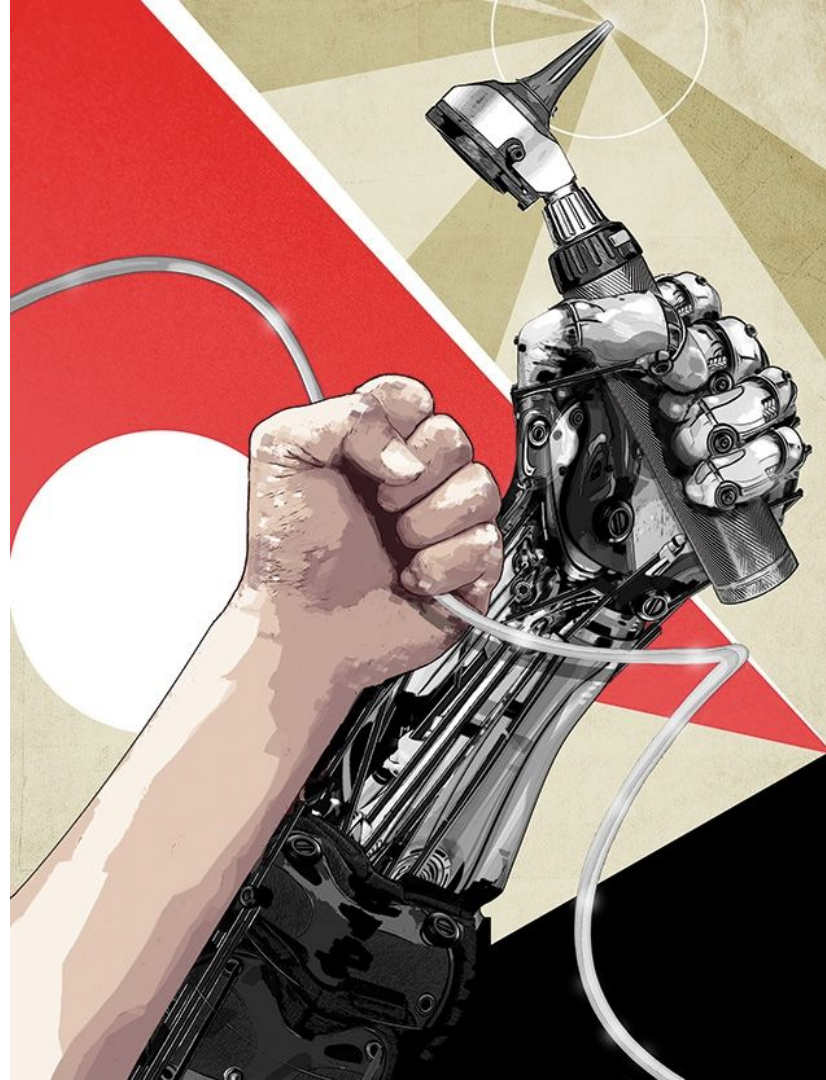
SVD (Singular Value Decomposition)



Practice!



Challenge!



Bibliografía

/1./ /Hands-on Machine Learning with Scikit-Learn, Keras, and TensorFlow/

/2./ /Fast.AI - Introduction to Machine Learning for Coders/

/3./ /MLCourse.AI/

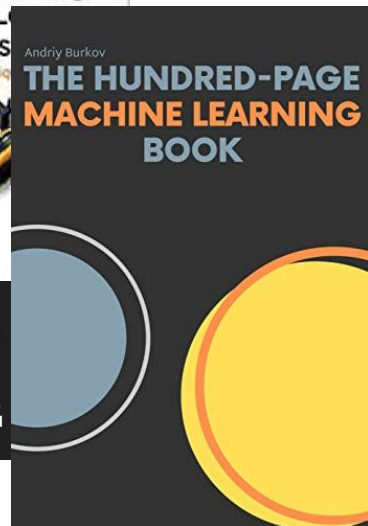
/4./ /DeltaAnalytics/

/5./ /The Hundred-page Machine Learning Book/

/6./ /Machine Learning for Humans (Vishal Maini)/

/7./ /Datacamp/

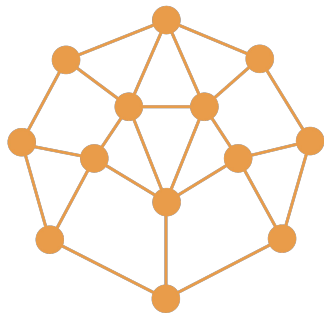
/8./ /DataQuest/



Partners

Agradecemos a nuestros partners por confiar en **nosotros** para facilitar la formación en **IA** de cara a la 4ª Revolución Industrial.





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This model fits me
95% of the time



WELCOME!



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